“Changing dividend payout behavior and predicting dividend policy in emerging markets: Evidence from India”

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CHANGING DIVIDEND PAYOUT BEHAVIOR AND PREDICTING DIVIDEND POLICY IN EMERGING MARKETS: EVIDENCE FROM INDIA

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Abstract

Dividends have become increasingly important for capital market participants to achieve financial goals in the rapidly changing Indian economy. This study aims to simplify the evolving Indian dividend puzzle by analyzing the dividend trends, examining the evolving nature of firm and macroeconomic determinants of dividends, and developing a dividend policy prediction model. Dividend trends of 3,162 non-financial listed Indian firms from 2006–2022 are studied to gain insights about the Indian dividend puzzle. Regularization and logit models are used to explore the nature of impact of important dividend determinants. Data-mining methods are employed to build a robust model for dividend policy prediction. Trend analysis reveals a decline in the quantum of dividends and proportion of dividend-paying firms with approximately 90% of the dividend-payers belonging to the manufacturing and service sector. Further findings suggest that size, age, maturity, profitability, past dividends, earnings, and bank monitoring of firms had a favorable impact on the likelihood of dividend payments. Macroeconomic indicators such as GDP growth rate, repo rate, percentage change in equity issues, listings, gross fixed assets formation also had a positive impact. The annual percentage change in debt issues and new project announcements at the macro level with investment prospects at firm level negatively impacted dividends. Dividend prediction model based on the random forest technique achieved the highest prediction accuracy of 90.77% and 77.31% under binomial and multi-class situations. These findings are expected to help corporate executives, portfolio managers and investors proactively design optimal dividend policies and formulate their investment strategies.

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INTRODUCTION

Dividends entail the distribution of surplus generated by business operations to shareholders. Although various studies have already examined the dividend phenomenon in India, in light of the various changes observed in the Indian economy in the recent past, it has become essential to revisit the dividend puzzle to provide further insights about its evolving nature. Indian firms frequently opt for regular dividends as a signaling tool for reducing the prevailing information asymmetry (Kim et al., 2021; Kanojia & Bhatia, 2023). An increase in participation of retail investors in the equity markets over the last two decades has further bolstered the importance of dividends in India. Majority of retail investors belong to middle income groups from small towns and prefer dividends over capital gains (Graham & Kumar, 2006). Additionally, disincentivizing of fixed income schemes like fixed deposits, Public Provident Fund (PPF), etc. have made dividends a preferred source of recurring income for retail investors. The low level of investor protection in India coupled with the growing retail investor base in the rapidly expanding Indian equity markets further adds to

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the rising concerns for protecting the shareholders' interests, particularly in the light of recent corporate governance scams. This further increases the relevance of dividends as an instrument for reducing agency problems by disbursing the excess cash to the shareholders (Pahi & Yadav, 2019). Enactment of the new Companies Act in 2013, adoption of the Indian Accounting Standards, increase in obligation of auditors and stricter corporate governance norms after the Satyam scam have further impacted the role of dividends as a substitute of governance mechanism in Indian firms. India has also experienced rapid changes in macro-level indicators alongside the changes in firm level characteristics in the past two decades. Interestingly, high GDP growth rate in India presents the twin contrary arguments of higher investments by firms resulting in lower dividends versus higher profits (propelled by higher growth) resulting in larger dividends. Additionally, the private sector has taken a greater role in the economy in the last twenty years. Private sector firms are highly growth-oriented and thus focus more on capital appreciation through reinvestments than on paying dividends. Further, there was a change in the dividend taxation policy in 2019–2020 that provides for the taxability of dividends in the shareholders' hands against the earlier law of dividends being exempt in the shareholders' hands. The drastic change in the economic and regulatory policy stance of the new government since 2014 and the impact of global shocks (financial crisis of 2008 and COVID-19 pandemic) have further made dividends a highly intriguing research issue. The earlier discussion indicates that the influence of the various determinants of dividends may have undergone a large change. The above context makes it essential to revisit the dividend puzzle amidst the new and increasingly changing economic setup in India. Also, despite the numerous market reforms to improve the information environment, dividends' ability to influence market value of share, especially in emerging markets with high information asymmetry highlights the importance of the need for dividend policy prediction in the Indian context.

1. LITERATURE REVIEW

The role and importance of dividends has changed with the evolution of the Indian economy. Its importance for protecting the interest of investors highlights its dual nature as an outcome and substitute of good governance. Agency hypothesis posits the use of a firm's resources on extravagant payments to managers and investment in bad projects (Jensen & Meckling, 1976; Manos, 2003). This results in the decline in firm value (Jensen, 1986). Effective governance prevents such misuse of funds and thereby results in higher dividends thus providing evidence for the outcome hypothesis (Sharma, 2011; Pahi & Yadav, 2019; Kanojia & Bhatia, 2022; Fayyaz et al., 2023). On the contrary, Benjamin and Jain (2015) found evidence of substitution argument between dividends and corporate governance in Indonesia. This is especially due to weak shareholder protection mechanisms in the developing markets. Further, Michiels et al. (2015) found that dividends are an effective tool to cool off the intra-family conflicts in a privately held firm. This relationship is strengthened by the governance practices of the family, which subsequently results in the increase in efficacy of dividend policies in minimizing agency issues. This points to the role of dividends as an agency problem trouble-shooter across all types of firms. Additionally, the evolving nature of financial markets has significantly impacted the signaling role of dividends.

Therefore, the trend in dividend payments and propensity to pay was investigated by various studies to understand the dynamic nature of dividends. Fama and French (2001) analyzed the dividend trend of US firms between 1926–1999 revealing a sharp fall in dividend paying firms post 1972 and especially after 1978. The study attributed it to the substantial increase in the newly listed firms that were smaller, had high growth rates and low earnings. A widespread decline in the propensity to pay amongst US firms was also noted. A decline in dividend-payers, combined with an increase in total dividends paid, further reflected the increase in the degree of concentration (Allen & Michaely, 1995). This decline was also explained by the increased substitution of dividends with share repurchases. Firms preferred offloading cash reserves through the share buyback route as it was more tax efficient than dividends. It also increased the EPS with the option of using repurchased shares for issuing employee stock options in future (Dittmar, 2008).

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Baker and Wurgler (2004) found a new aspect in the form of adjustments in the market dividend premiums by investors to be the reason for the disappearing and reappearing pattern in dividends. Another study by Bates et al. (2009) further explained that the decreasing trends in dividends was also due to the high cash holdings by firms because of the increased riskiness and requirement of timely payment of debt.

Ferris et al. (2006) examined the declining dividend pattern among UK firms and found a drop in dividend-paying firms from 75.9% to 54.5%. Unlike US, tax policy amendments and substitution effect of repurchases could not explain this trend. Rather, the catering hypothesis by Baker and Wurgler (2004) seemed to strongly drive the dividend payments.

Denis and Osobov (2008) analyzed a dataset of multiple countries to test the global presence of disappearing dividends. They also found evidence of declining propensity to pay dividends along with the concentration phenomenon across US, Canada, France, UK, Germany, and Japan during 1989 to 2002. Similar cross-country analysis by Vieira and Raposo (2007) suggested that the trend was different across UK, France, and Portugal during 1994–2002. They found no decline in case of France but highly erratic dividend stream in case of Portugal, thereby indicating varying trends across economies with different characteristics. Another study by Ferris et al. (2009) examined the disappearing dividends across 25 countries and found that propensity to pay had declined more in common law countries than civil law countries during 1994–2007. However, an extensive study covering 33 nations by Fatemi and Bildik (2012) found the decline to be more prominent in weak investor protection nations with civil law.

Also, the long-established linkage between dividends and future earnings was negated and along with share repurchase substitution raised a question on their signaling use (Grullon & Michaely, 2002; Grullon et al., 2005). Dividend-increasing firms experienced a decline in market risk and an increase in future prices (Grullon et al., 2002). However, another study suggested that the use of dividends (firms experiencing regular stable cash flows) and stock repurchases (firms with non-recurring non-operating cash flows) were done by firms with different characteristics and thus are not substitutes (Jagannathan et al., 2000).

Although, it was well established that propensity to pay dividends had decreased, but a study by Grullon et al. (2011) suggested an increase in net cash disbursements to shareholders through other routes during the same time. This highlighted the shift in preference of firms from dividends to other ways of distributing cash to shareholders. However, dividend payments bounced back in the early years after 2000 due to an increase in the maturity of newly listed firms and restoring of investor confidence by reduction in the investment in wealth destroying projects. It was further supported by the tax rate cut of 2003 (Julio & Ikenberry, 2004).

The change in propensity to pay dividends was observed across 18 economies in another study by Kuo et al. (2013). It was impacted by risk and liquidity with catering playing an important role in the risk-reward criterion especially in the high investor protection regimes of common law economies.

Michaely and Moin (2022) enlarged the time frame of the analysis by studying dividend pattern from 1970 to 2018 and found that dividend decline was partly due to changes in firm characteristics and partly due to changing firm tendency. The reappearance of dividends, post 2000 was due to delisting of non-paying firms at a fast pace. Banks on the contrary did not exhibit any decline in dividends since 1978 till the onset of crisis in 2008. Later, banks resorted to aggressive reductions to preserve and support capital requirements after the crisis deepened (Floyd et al., 2015).

Developing economies on the other side had a different experience. Higher propensity to pay was manifested in the form of dividends by state-owned firms in China as a tunnelling tool rather than to alleviate the agency costs of minority shareholders (Lee & Xiao, 2004). Additionally, leverage, growth opportunities, concentrated ownership and smoothened dividends played a crucial role in the payment of dividends in excess of the regulatory requirement in Brazil (Procianoy & Vancin, 2014).

India experienced the dividend-disappearance phenomenon during 1995–2002, reappearance between 2003–2008 and repeat of disappearance from 2009–2013. Dividend payout ratio and dividend yield showed a volatile path during 1995–2013. The number of dividend-payers had decreased but not as strongly seen in the developed world. Similar to the earlier findings in the developed countries, concentration of earnings and dividends with increase in aggregate dividends and earnings was experienced in India during that period. However, dividend payers experienced higher growth than non-payers in India as opposed to the findings in the developed countries. Catering considerations also seemed to have a significant influence on the propensity to pay dividends (Labhane, 2017). Another study on India by Pahi and Yadav (2021) revealed that dividend tax was the major culprit of decline in the propensity to pay dividends. Effective governance mechanisms gave a boost to dividends during 1990–2016. They found dividends to appear, disappear and followed by reappearance in later part of the time period 1990–2016.

Thus, the earlier discussion points to the varied dividend trends observed across time and region, which triggers the need for dividend policy prediction. Only a few studies in the past have attempted to build empirical models to achieve this objective. Three separate studies used data-mining techniques on a small sample of 137 listed Korean companies from 1980–2000 to predict the dividend policy under a binary classification scenario of dividend-payers and non-payers. Bae (2010) found support vector machine (SVM) to achieve the highest accuracy. Kim et al. (2010) found knowledge integration (KI) method to be more accurate than decision tree (DT) and neural networks (NN). Subsequently, Won et al. (2012) found genetic algorithm-based knowledge refinement (GAKR) to give the highest prediction accuracy.

Longinidis and Symeonidis (2013) used DT and NN on a sample of 244 Greek companies from 2007–2009 to predict dividend policy in a binary class scenario and compared the results with logistic model. DT and NN were found to be far more accurate. Further, Kosala (2017) also found DT to more accurately predict the likelihood of paying dividends in comparison to SVM, logistic regression and multi-layer processing (MLP) in the context of 366 Indonesian listed firms between 2007–2009.

The above discussion suggests that the nature of disappearing dividends phenomenon has changed with the passage of time. There is also a dearth of literature on empirical analysis deciphering the dividend puzzle particularly in India after the numerous changes observed in the Indian economy along with the global shocks in the form of COVID-19 crisis and geopolitical tussles. These events along with world economic slowdown and rising Indian stock markets further adds to the complexity of the issue. Increased understanding of the dividend puzzle will have wider implications for market participants. It will also help in accurate prediction of dividend policy of firms. Lack of accurate prediction models impair efficient investment and financial planning by various financial market participants. Therefore, this study tries to find answers to the existing gaps in the literature. Specifically, this study aims to examine the changes in the dividend pattern in India, investigate the evolving role of micro and macro-level determinants of dividend on the likelihood of dividend payments by Indian firms and develop a dividend policy prediction model in the Indian context.

2. METHODS

Initial sample of the study included all non-financial Indian companies listed on the National Stock Exchange and Bombay Stock Exchange. The sample period from 2006–2022 was covered to analyze the impact of major shift in the business environment in India over the last two decades. Companies with missing data for large number of years were excluded with 3,162 companies remaining in the final sample. The factors that are studied for analyzing the likelihood to pay dividends and further for dividend policy prediction are determined from an exhaustive set of potential dividend-influencing variables. These variables capture firm level characteristics, macroeconomic indicators, and crisis shocks of 2007–2008 (financial crisis) and 2019–2020 (COVID pandemic). Equity dividend to the net worth ratio was used as the dependent variable representing dividend payments. All the variables used in the study have been explained in Appendix, Table A1. All the company specific continuous variables were winsorized at the 5^{th} and 95^{th} percentile values to remove the effect of outliers. Data for firm-level variables was extracted from the Prowess IQ database maintained by Centre for Monitoring Indian Economy (CMIE). Data of macroeconomic variables was obtained from CMIE Economic Outlook and RBI database.

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The paper examined the dividend trends from 2006–2022 to understand the evolving behavior and characteristics of dividends in India. Number of firms, proportion of firms, proportion of firms with positive and negative earnings and industry composition was calculated on annual basis. These calculations were performed for both dividend-paying and non-paying firms to capture the different aspects of dividend trends. Yearly mean, standard deviation and quartile values were calculated for equity dividend to net worth ratio and dividend payout ratio to study the trend in size of payout by firms during the sample period.

Regularization techniques consisting of ridge regression (Hoerl & Kennard, 1970), five approaches (cross-validation (CV), adaptive, plugin, Bayesian Information Criterion-BIC and square-root) of lasso regression (Tibshirani, 1996; Hastie et al., 2015) and elastic net regression (Zhou & Hastie, 2005; Zhou, 2013) were used to select the determinants with the maximum out of sample prediction. A final dataset was divided into training and testing sets having equal data points with 10-fold cross-validation. Logistic regression was used for investigating the impact of selected determinants on the likelihood to pay dividends (Labhane, 2017; Pahi & Yadav, 2019). Logit regression model is represented by equation 1:

$$Y_{it} = \log_{it}\left(\beta_0 + \beta_1 X_{1it} + \beta_2 X_{2it} \ldots + \beta_n X_{nit} + \varepsilon_{it}\right), \quad (1)$$

where Y_{it} takes a value equal to one if the firm pays dividend in a year, and zero otherwise. X_{1it} to X_{nit} represent the independent variables determining dividends. β_0 is the constant term and β_1 to β_n are the coefficients that indicate the change in the probability to pay dividends with a unit change in the respective variable, $\boldsymbol{\varepsilon}_{it}$ represents the prediction errors.

Further, two most parsimonious set of determinants selected by regularization techniques were deployed in data-mining techniques to develop dividend policy prediction models. Six data-mining techniques consisting of linear discriminant analysis (LDA), logistic regression (Logit), decision tree (DT), K nearest neighbors (KNN), support vector machine (SVM) and random Forest (RF) were used for this purpose. DT has been earlier used for dividend policy prediction by studies on Korea (Bae, 2010; Won et al., 2012). SVM has been used for dividend classification problem in studies on Indonesia and Egypt (Kosala, 2017; Elyasiani et al., 2019). Dividend policy prediction was categorized into binary and multiclass scenarios. Binary scenario was represented by classification of firms into dividend-paying (represented by 1) and non-paying firms (represented by 0) in each year. This was done to develop a model for predicting whether a firm will pay dividend in a particular year or not. Further, the multi-class dividend prediction scenario transformed the dividend policy changes into five categories of zero dividend in the previous year to positive dividend in the current year, current year dividend was greater than last year dividend, current year dividend was same as last year dividend, current year dividend was less than last year dividend and dividend in the previous year to zero dividend in the current year. These five categories were represented by five categorical variables of 2, 1, 0, –1 and –2. These categories captured if the dividend was initiated, increased, constant, decreased or stopped. SVM, KNN, Logit, RF and DT techniques were used for predicting these five changes in dividend payments. Data was divided into two sets of training and testing data with each set containing 50% observations. Five-fold cross-validation was used for obtaining the results. Grid search was employed to find out the optimal value of the hyper-parameter for all the techniques used in dividend policy prediction under binary and multi-class scenarios. Linear kernel function was found to be appropriate for SVM. The cost function (C) was selected from a range of 0.1, 1, 10, 100 and 1000 for SVM and Logit. Range of 1 to 25 and 2 to 100 was taken for KNN and DT to find the optimal value of K=nearest neighbors and maximum depth. Range for the number of trees in RF was 100 to 1,000 with an interval of 100. Singular value decomposition solver was used in LDA as it does not compute the covariance matrix and thus is appropriate for a model with a large number of features.

3. RESULTS

Dividend trend analysis in Table 1 shows that the number of dividend-paying firms increased slightly from 629 in 2006 to 692 in 2022 with a mixed trend during the period. It declined to the lowest number of 509 in 2021 due to the uncertain future posed by the covid pandemic. The number of non-payers on the contrary continuously increased from 202 firms in 2006 to 1,051 firms in 2021. The opening of the economy in 2022 after the COVID pandemic and lesser growth opportunities in the near future boosted dividends. This decreased the non-payers to 825 in 2022. Results also reveal that percentage of payers declined from 75.69% in 2006 to 45.62% in 2022. The decrease in dividend-payers and increase in non-payers was a result of newly listed firms failing to initiate dividends due to lower profits and higher growth needs.

Table 1. Dividend payer and non-payer firm composition

Year	No. of Payer Firms	No. of Non-Payer Firms	Total Firms	Payers (in %)	Non-Payers (in %)
2006	629	202	831	75.69	24.31
2007	624	206	830	75.18	24.82
2008	703	210	913	77	23
2009	668	246	914	73.09	26.91
2010	725	284	1009	71.85	28.15
2011	741	380	1121	66.1	33.9
2012	683	464	1147	59.55	40.45
2013	673	467	1140	59.04	40.96
2014	685	516	1201	57.04	42.96
2015	747	686	1433	52.13	47.87
2016	719	693	1412	50.92	49.08
2017	533	841	1374	38.79	61.21
2018	634	653	1287	49.26	50.74
2019	646	663	1309	49.35	50.65
2020	669	890	1559	42.91	57.09
2021	509	1051	1560	32.63	67.37
2022	692	825	1517	45.62	54.38

Trends in size (equity dividend to net worth ratio and dividend payout ratio) of dividends are provided in Table 2. Dividend as a percentage of net worth continuously decreased from 3.85% in 2006 to 2.65% in 2015. Except in 2016 and 2020, it followed the declining path with a rise in 2022. 26.35% of profits was paid as dividends in 2006 which declined till 2008 and increased in 2009. This was due to the lower denominator effect (profits) and higher dividends due to bleak growth avenues arising out of the financial crisis. The fall in dividend payout ratio continued till 2013 to reach 23.89%. It rose for the next 3 years to reach 25.1% in 2016. It fell thereafter before rising sharply to reach 27.98% in 2020 (low denominator effect) and then fell sharply again to reach 19.95% in 2022. The top 25% of the firms paid very large dividends as can be seen in quartile 3 values for both the measures of dividend payments (equity dividend to net worth ratio and dividend payout ratio). This highlights the concentration of dividends amongst the top quartile firms.

Table 2. Trends in dividend payouts

Equity Dividend to Net Worth							
Year	No. of Payers	Mean	Std dev	Min	Q1	Q2	Q3
2006	629	0.0385	0.0189	0.0012	0.0229	0.0356	0.0577
2007	624	0.0374	0.0194	0.0022	0.0214	0.0341	0.0563
2008	703	0.0338	0.0194	0.0019	0.0176	0.0298	0.0506
2009	668	0.0291	0.0188	0.00E+00	0.0142	0.0245	0.0414
2010	725	0.0309	0.0191	0.0009	0.0149	0.0259	0.0452
2011	741	0.0303	0.0195	0.0009	0.0145	0.0249	0.0444
2012	683	0.0291	0.0198	0.0011	0.0135	0.023	0.0433
2013	673	0.0271	0.0189	0.0007	0.0117	0.0215	0.0389
2014	685	0.027	0.0194	0.0006	0.0119	0.0216	0.0389
2015	747	0.0265	0.0189	0.0009	0.012	0.0206	0.0365
2016	719	0.0275	0.0194	0.0009	0.0118	0.0222	0.0384
2017	533	0.0233	0.0187	0.0001	0.009	0.0168	0.0314
2018	634	0.0235	0.0182	0.0008	0.0095	0.0178	0.0312
2019	646	0.024	0.0187	0.0008	0.0099	0.0184	0.0334
2020	669	0.0315	0.0221	0.0008	0.0128	0.0254	0.0524
2021	509	0.0216	0.0197	0.0003	0.007	0.0143	0.0296
2022	692	0.0246	0.0205	0.0002	0.0083	0.0178	0.0352
Dividend Payout Ratio							
Year	No. of Payers	Mean	Std dev	Min	Q1	Q2	Q3
2006	622	26.35	13.72	1.84	15.07	23.57	36.8
2007	618	24.23	13.36	1.13	13.25	22.85	32.07
2008	693	22.99	13.87	1.13	11.83	19.71	30.47
2009	644	24.48	14.42	1.62	12.43	21.84	34.11
2010	700	22.55	13.15	1.06	11.82	20.24	30.51
2011	724	22.4	13.49	1.06	11.7	19.13	30.29
2012	663	23.99	13.86	1.05	13.25	20.95	32.41
2013	652	23.89	13.98	1.25	12.65	21	32.86
2014	654	24.31	13.8	1.21	12.79	21.61	33.47
2015	714	24.52	13.88	1.37	13.62	22.26	33.39
2016	684	25.1	14.68	1.51	12.33	22.4	36.13
2017	513	21.42	15.35	0.41	8.68	17.06	31.33
2018	607	21.22	14.47	0.55	9.79	17.35	30.5
2019	612	21.6	15	0.51	9.17	17.77	31.4
2020	627	27.98	16.63	0.41	12.88	26.17	49.61
2021	477	19.83	16.21	0.39	6.85	13.46	29.9
2022	669	19.95	15.99	0.06	6.34	14.99	29.99

Note: Table 2 provides the annual mean values, standard deviation, minimum and quartile values for equity dividend to net worth ratio and dividend payout ratio.

Table 3 shows that the percentage of payers with positive EPS (earnings per share) have been in range of 95% to 98%. Non-payers with positive

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EPS decreased in the initial 8 years from 99.01% in 2006 to reach 56.75% in 2013 and then it increased in the future years to reach 76.36% in 2022. Growth in the proportion of firms with negative EPS both amongst dividend-payers and non-payers also led to decrease in the proportion of dividend-payers and size of dividends. Industry composition of dividend-paying and non-paying firms in Table 4 suggests that more than 90% of payers approximately were from the manufacturing and service sector. The share of manufacturing sector decreased, and the share of service sector increased by the same quantum amongst dividend-paying firms. Real estate consisted of 4%-9% of payers. Electricity and mining comprised 1%-2% of payers.

Table 3. Decomposition of payers and non-payers into firms with positive and negative EPS

Year	Dividend-Payers		Dividend Non-Payers	
	% of firms with negative EPS	% of firms with positive EPS	% of firms with negative EPS	% of firms with positive EPS
2006	0.95	99.05	0.99	99.01
2007	0.32	99.68	0.97	99.03
2008	0.71	99.29	2.86	97.14
2009	3.29	96.71	18.7	81.3
2010	1.1	98.9	26.76	72.54
2011	1.48	98.38	29.47	70
2012	2.05	97.66	37.5	62.07
2013	1.78	98.22	42.4	56.75
2014	3.5	95.91	41.09	57.75
2015	2.68	96.92	39.36	59.91
2016	3.76	96.24	34.92	64.5
2017	2.25	97.75	28.66	70.63
2018	2.68	97.16	28.79	71.06
2019	3.72	96.28	30.77	68.63
2020	5.08	94.92	35.84	63.82
2021	2.75	97.25	28.35	71.55
2022	2.46	97.54	23.52	76.36

Note: Table 3 presents the proportion of firms with positive and negative EPS amongst dividend-payers and non-payers on yearly basis.

Comparison of firm characteristics (annual mean values) of dividend-payers and non-payers reveals that investment prospects of payers were 1.5 times higher than non-payers with greater increase seen amongst non-payers. Sales growth for payers has been higher than non-payers except in 2022 with visible trend of decline in the difference amongst them. Return on assets and EPS of payers has been five to eight times higher than non-payers during the sample period. Beta and change in profits have been observed to be higher for payers than non-payers except in the initial years of the study period. This is different from the findings of the developed world (Fama & French, 2001; Denis & Osobov, 2008) and has been found to be more evident after the financial crisis of 2007–2008 to 2009–2010. Liquidity of payers became greater than non-payers after 2013 and free cash flows of payers was mostly greater than non-payers during the sample period. Payers were much larger in size and have half the leverage than non-payers. Liquidity of shares of payers ranges on an average between one-third to one-fifth of the non-payers thereby reducing the need for non-payers to pay dividends. The tangibility of payers was slightly less than non-payers till 2014 and thereafter it was slightly higher for them. Payers were older and more mature than non-payers. Retained profits share in the equity increased from more than 50% to 80% for payers whereas it increased from close to 15% to 31% for non-payers during the sample period. Effective tax rate was higher for the payers whereas greater proportion of shareholding was owned by institutions and promoters in payers than non-payers. Institutional stake was more than double of that of non-payers whereas the difference in promoter stake was small. Both have raised majority of debt from banks and the payers had a greater number of banking relations indicating better bank monitoring of operations of payers.

Descriptive statistics consisting of number of observations, mean, standard deviation, minimum and maximum values of the variables are provided in table 5. The absence of the multi-collinearity was indicated by low correlation (less than ± 0.8) between the independent variables. Table 6 presents the two most parsimonious set of dividend-determining variables identified by regularization techniques. Plugin and BIC lasso selected the most parsimonious model with 19 (Sparse Model 1) and 24 (Sparse Model 2) determinants. These are further employed in the logit model to gauge their impact on the likelihood to pay dividends. They are also used in the dividend policy prediction models under binary and multiclass scenarios.

Table 6 also provides the results of logistic regression analysis that shows the nature of impact of variables selected by plugin and BIC lasso on the

Table 4. Industry composition

Payers Industry Composition (in Percent)						
Year	**Manufacturing**	**Services**	**Real Estate**	**Electricity**	**Mining**	**Total**
2006	79.81	13.83	4.62	0.79	0.95	100
2007	79.17	13.78	5.29	0.8	0.96	100
2008	75.96	15.08	6.54	1	1.42	100
2009	74.55	15.57	7.78	1.05	1.05	100
2010	73.1	15.86	8.83	1.11	1.1	100
2011	74.36	14.71	8.77	0.95	1.21	100
2012	73.79	16.4	8.05	0.88	0.88	100
2013	74.89	15.75	7.28	1.34	0.74	100
2014	74.02	16.2	7.15	1.75	0.88	100
2015	74.56	16.47	6.56	1.61	0.8	100
2016	75.52	15.99	5.98	1.53	0.98	100
2017	74.48	16.14	6.75	1.5	1.13	100
2018	75.71	14.82	6.47	1.42	1.58	100
2019	76	15.48	5.73	1.24	1.55	100
2020	75.19	18.39	4.04	1.04	1.34	100
2021	74.85	18.47	4.13	0.98	1.57	100
2022	76.73	16.47	4.48	0.87	1.45	100
Non-Payers Industry Composition (in Percent)						
Year	**Manufacturing**	**Services**	**Real Estate**	**Electricity**	**Mining**	**Total**
2006	72.28	21.29	4.95	0	1.48	100
2007	66.02	26.7	4.85	0.49	1.94	100
2008	67.62	25.71	5.24	0.48	0.95	100
2009	66.67	28.05	4.07	0.4	0.81	100
2010	63.73	29.93	4.23	1.41	0.7	100
2011	64.74	28.16	5.52	1.05	0.53	100
2012	65.95	26.29	6.46	0.65	0.65	100
2013	61.46	28.05	9.21	0.64	0.64	100
2014	62.99	26.55	8.91	0.97	0.58	100
2015	59.47	30.03	9.04	1.02	0.44	100
2016	60.03	28.43	9.67	1.15	0.72	100
2017	62.55	27.59	8.2	0.95	0.71	100
2018	60.64	29.41	8.42	0.92	0.61	100
2019	60.94	28.96	8.14	1.21	0.75	100
2020	59.44	29.66	8.99	1.01	0.9	100
2021	63.65	26.07	7.99	1.24	1.05	100
2022	58.91	29.82	8.85	1.45	0.97	100

Note: Table 4 presents the proportion of firms from manufacturing, service, real estate, electricity and mining sectors amongst dividend-payers and non-payers on yearly basis.

Table 5. Descriptive statistics

S.No	Variable	Observations	Mean	Std. dev.	Min	Max
1	EDNW	47,637	0.0109525	0.0189026	0	0.0661157
2	$EDNW_{t-1}$	46,693	0.0115254	0.0194515	0	0.0669092
3	PB	35,764	2.045122	2.18798	0.16	8.35
4	DNS	46,666	0.1361505	0.4789941	–0.8064516	1.503963
5	ROA	48,612	2.276072	7.694348	–18.67	16.65
6	EPS	46,635	7.571439	14.48812	–8.74	53.51
7	BETA	35,365	0.9030488	0.4540727	0.02	1.7
8	DPAT	48,015	0.2499919	1.647414	–3.582011	4.541935
9	CR	49,034	2.025202	2.298932	0.22	10.86
10	NCMC	36,147	0.0041069	0.0748079	–0.1832461	0.2045954
11	NS	46,771	6.65441	2.396033	0.9932517	10.28458

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Table 5 (cont.). Descriptive statistics

S.No	Variable	Observations	Mean	Std. dev.	Min	Max
12	DE	45,646	0.9098252	1.123067	0	4.28
13	STMC	38,767	29.61407	62.15196	0.0308375	261.5945
14	AGE	52,261	3.17293	0.7116772	0	5.068904
15	CRENW	49,559	0.4413504	0.7121474	–1.531646	2
16	TANG	49,569	0.2715646	0.2046952	0	0.6952459
17	CTPBT	48,958	16.50569	14.17526	0	40.33
18	NPI	39,559	6.685686	9.773294	0	32.3
19	PRO	44,258	53.52051	17.19729	14.97	75
20	BDTD	44,507	0.570218	0.3749459	0	1
21	NB	36,211	4.021292	4.220793	1	51

Note: See Appendix, Table A1 for variable description and variable identification codes. The table shows the number of observations, mean, standard deviation, minimum and maximum value for all the firm-specific continuous variables.

chances of dividend payment. Logit results of sparse model 1 found government stake and audit quality coefficients to be insignificant at 5% significance level. The overall model was highly significant, and the pseudo r square was 54.08%. Audit quality coefficient was positive and significant at the 10% level. This finding was similar in sparse model 2. Sparse model 2 found government stake, TRR3 (last dividend tax rate regime), current ratio, annual percentage change in debt issues and

Table 6. Variables selected by regularization methods and logit results of the two sparse models

S.No.	Variable	Determinants selected by Plugin lasso	Logit Results (Sparse Model 1)- Direction of impact with significance of selected variables	Determinants selected by BIC lasso	Logit Results (Sparse Model 2)- Direction of impact with significance of selected variables
1	$EDNW_{T-1}$	x	Positive ***	x	Positive ***
2	EPS	x	Positive ***	x	Positive ***
3	PB	x	Negative **	x	Negative **
4	ROA	x	Positive ***	x	Positive ***
5	DPAT	x	Positive ***	x	Positive ***
6	CR			x	Positive
7	AGE	x	Positive ***	x	Positive ***
8	CRENW	x	Positive ***	x	Positive ***
9	NS	x	Positive ***	x	Positive ***
10	CTPBT	x	Positive ***	x	Positive ***
11	TRR_3			x	Positive
12	AUDIT	x	Positive *	x	Positive *
13	NPI	x	Positive ***	x	Positive ***
14	Ownership	x	Negative	x	Negative
15	MANU			x	Negative ***
16	BDTD			x	Positive ***
17	GDP	x	Positive ***	x	Positive ***
18	REPO			x	Positive ***
19	GDPM3	x	Positive ***	x	Positive ***
20	EQ	x	Positive ***	x	Positive ***
21	DEBT	x	Negative ***	x	Negative
22	NL	x	Positive ***	x	Positive ***
23	GFA	x	Positive ***	x	Positive ***
24	IP	x	Negative **	x	Negative
Total number of selected determinants		19		24	
Number of Observations			29063		26636
Prob>chi^2			0.0000		0.0000
Pseudo R^2			0.5408		0.5313

Note: Legend x represents the variables selected as determinants by Plugin and BIC lasso. The variable codes and definition can be referred from Appendix, Table A1. Symbols ***, ** and * indicate significance at 1%, 5% and 10%, respectively.

new project announcements to be insignificant. The overall model was highly significant, and the pseudo r square was 53.13%. Coefficients of past year dividends, profitability, current year earnings, size, age, maturity, effective tax rate, institutional stake holding, bank monitoring, GDP growth rate, repo rate, income velocity of money, annual percentage change in equity issues, listings, and gross fixed assets formation were positive and significant at 5% significance level. Coefficients of investment opportunities available to the firm, annual percentage change in debt issues and new project announcements at macro-level were negative and significant at the 5% significance level.

Further, output results for dividend policy prediction under binary class scenario with the two parsimonious set of determinants identified by regularization methods are compared based on prediction performance measures such as cross-validation (CV) mean-score, accuracy, brier score, precision, recall and f1-score of testing data. Cross-validation mean score tells the average correct prediction score of the various samples created by cross-validation. Accuracy is the percentage of correct predictions made of total prediction (sum of true positives and true negatives divided by total observations). Brier score measures the accuracy of prediction by calculating the square of the difference between the probability of prediction

Table 7. Binomial scenario dividend policy prediction results

Sparse Model 1 (19 determinants selected by Plugin Lasso)											
No. of Observations = 29,063											
Technique	**Best Parameter**	**AUC**	**Cross Validation Mean Score**	**Accuracy**	**Brier Score**	**Precision (0)**	**Precision (1)**	**Recall (0)**	**Recall (1)**	**F1 Score (0)**	**F1 Score (1)**
Support Vector Machine	Linear Kernel, C = 0.1	0.87	0.875	0.8739	0.1261	0.87	0.88	0.88	0.87	0.87	0.88
K Nearest Neighbor	N Neighbors = 24	0.81	0.8073	0.8092	0.1908	0.81	0.81	0.81	0.81	0.81	0.81
Logistic regression	C = 1000	0.8	0.7952	0.8037	0.1963	0.81	0.8	0.79	0.82	0.8	0.81
Random Forest	N Estimators = 900	0.91	0.9112	0.9077	0.0923	0.9	0.91	0.91	0.91	0.9	0.91
Linear Discriminant Analysis	Solver = SVD	0.87	0.8697	0.8701	0.1299	0.85	0.89	0.89	0.85	0.87	0.87
Decision Tree	Max Leaf Nodes= 41	0.9	0.9059	0.8993	0.1007	0.91	0.89	0.88	0.92	0.9	0.9
Sparse Model 2 (24 determinants selected by BIC Lasso)											
No. of Observations = 26,636											
Technique	**Best Parameter**	**AUC**	**Cross Validation Mean Score**	**Accuracy**	**Brier Score**	**Precision (0)**	**Precision (1)**	**Recall (0)**	**Recall (1)**	**F1 Score (0)**	**F1 Score (1)**
Support Vector Machine	Linear Kernel, C = 100	0.87	0.8694	0.8704	0.1296	0.86	0.89	0.88	0.86	0.87	0.87
K Nearest Neighbor	N Neighbors = 21	0.81	0.8018	0.8081	0.1919	0.8	0.82	0.81	0.81	0.87	0.81
Logistic regression	C = 1000	0.8	0.7997	0.8032	0.1968	0.8	0.8	0.79	0.82	0.87	0.81
Random Forest	N Estimators = 300	0.91	0.9056	0.9073	0.0927	0.9	0.91	0.91	0.91	0.9	0.91
Linear Discriminant Analysis	Solver = SVD	0.86	0.8642	0.8637	0.1363	0.84	0.89	0.9	0.83	0.87	0.86
Decision Tree	Max Leaf Nodes = 8	0.9	0.8989	0.898	0.102	0.87	0.92	0.92	0.87	0.87	0.9

Note: AUC – Area under the curve. Cross validation mean score, accuracy, precision, recall and F1 score values are out of 1. 0 in precision, recall and F1 score represent the values for dividend not paid category, and 1 represents values for the dividend paid category.

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Table 8. Multiclass scenario dividend policy prediction results

Technique	Sparse Model 1		Sparse Model 2	
	No. of Observations = 27,946		No. of Observations = 25,540	
	Cross Validation Mean Score	Accuracy	Cross Validation Mean Score	Accuracy
Support Vector Machine	0.6212	0.6309	0.6349	0.6366
K Nearest Neighbor	0.58	0.5911	0.578	0.5728
Logistic regression	0.564	0.5705	0.5723	0.5682
Random Forest	0.7659	0.7731	0.7614	0.7577
Decision Tree	0.7467	0.7548	0.7486	0.7479
Cross-validation mean score and accuracy values are out of 1				

Best Hyper-Parameter for the 2 Sparse Models		
Technique	Sparse Model 1	Sparse Model 2
Support Vector Machine	C = 100	C = 1000
K Nearest Neighbor	N Neighbors = 24	N Neighbors = 14
Logistic regression	C = 100	C = 100
Random Forest	N Estimators = 300	N Estimators = 200
Decision Tree	Max Depth = 6	Max Depth = 6

Note: Grid search was used to determine the best value for hyper-parameter in each technique.

and actual outcome. Therefore, it ranges between 0 and 1 and a low score reflects a higher accuracy, and vice versa. Precision measures the percentage of correct true positives out of total true positives predicted. Sensitivity or recall measures the true positive rate (predicted true positives divided by actual positives). F1-score reflects the average of both precision and recall (twice precision multiplied by recall divided by the sum of precision and recall). Binary scenario dividend policy prediction results are shown in Table 7. The cross-validation average prediction, accuracy and brier score of RF were 91.12%, 90.77%, and 0.0923. The CV mean-score and accuracy of DT were 90.59% and 89.93% with brier score at 0.1007. The accuracy of SVM, LDA, KNN and logistic models were 87.39%, 87.01%, 80.92% and 80.37%.

Results of sparse model 2 provided in Table 7 show that RF has a CV mean-score, accuracy and brier score of 90.56%, 90.73% and 0.0927. The accuracy was 89.8%, 87.04%, 86.37%, 80.81% and 80.32% for DT, SVM, LDA, KNN and logistic models, respectively. The precision, recall and f1-score for both the categories (dividend paid represented by 1 and not paid by 0) were close to each other and were also similar to the accuracy score. This shows the robustness of the models for prediction of both categories. F1-score was substantially higher for dividend not paid) in KNN and logistic models for sparse model 2. Table 7 also provides the best hyper-parameter value selected by grid search for each technique. The cost function (C) selected with sparse model 1 and 2 was 0.1 and 100 for SVM, and 1000 for logit. The optimal value for number of nearest neighbors was 24 and 21 for KNN with both the parsimonious set of determinants. The number of N estimators or trees for RF was 900 and 300 whereas the optimal value of max leaf nodes was 41 and 8 for DT.

Table 8 presents the CV mean score, accuracy, and best hyper-parameter value for all the five techniques used for dividend policy prediction under multi-class scenario. CV mean-score and accuracy were 76.59% and 77.31% for RF and 74.67% and 75.48% for DT in sparse model 1. The accuracy was 63.09%, 59.11% and 57.05% for SVM, KNN and logistic models. RF, DT, SVM, KNN and logistic have an accuracy of 75.77%, 74.79%, 63.66%, 57.28% and 56.82% for sparse model 2.

Table 8 also provides the best hyper-parameter value based on the application of grid search for each technique under multiclass scenario. The cost function (C) selected with sparse model 1 and 2 was 100 and 1,000 for SVM, and 100 for logit. The optimal value for number of nearest neighbors was 24 and 14 for KNN with both the sparse set of determinants. The optimal number of N estimators or trees for RF was 300 and 200, whereas the optimal value of max leaf nodes was 6 for DT.

4. DISCUSSION

This study examined the dividend puzzle during the last two decades that witnessed large-scale changes in the Indian and global economy. Trend analysis showed a slight increase in the number of payers despite a large change in the number of total firms. This translated into decline in the proportion of dividend-payers from 75.69% in 2006 to 45.62% in 2022. This was further evident in the decline in the size of dividend payments represented by equity dividend to net worth and dividend payout ratio which fell from 3.85% to 2.46% and 26.35% to 19.95% during the same time. The decline was not continuous and had periods of increase in between similar to the study by Pahi and Yadav (2021). The trend was not as strong as observed in the previous studies (Fama & French, 2001; Labhane, 2017). An increase in the number of negative EPS firms also supported the declining dividend phenomenon.

Further, logit analysis using the dividend determinants selected by regularization techniques suggested that audit quality increases the likelihood of dividends thereby confirming to the outcome hypothesis of corporate governance (Pahi & Yadav, 2019). Past dividends, profitability, current earnings, size, age, and maturity increased the chances of paying dividends, thereby confirming to the dividend smoothening, signaling and life cycle theory (Labhane, 2017; Pahi & Yadav 2021). Firms with ample investment prospects retain profits and thus it implies a decline in the chances of dividend payments (Labhane, 2017; Pahi & Yadav 2021). Effective tax rate, institutional stake holding and strong bank monitoring at the firm level were found to increase the chances of dividend payments. Macroeconomic indicators consisting of GDP growth rate, repo rate, income velocity of money, annual percentage change in equity issues, listings, and gross fixed assets formation were found to increase, while annual percentage change in debt issues and new project announcements were found to decrease the likelihood to pay dividends. These findings substantially add to the existing literature as their impact was not investigated by the previous studies. These results give insight into the dividend pattern and the evolving role of old and new factors impacting dividends (firm specific and macro-level). Later, various data-mining techniques were used to build a highly accurate dividend policy prediction model. RF gave the highest accuracy of 90.77% and 90.73% under binary class scenario. Bae (2010), Won et al. (2012), Longinidis and Symeonidis (2013), and Kosala (2017) achieved a prediction accuracy of 74.59%, 74.16%, 89% and 81.62% for the binary scenario. Accuracy of the model given by this study was higher than the previous studies because the optimal set of determinants used in prediction were selected from a more exhaustive list using regularization-based feature selection techniques. The results of the study have wider application as the dataset used in the study was larger than the previous studies. This study also extended the prediction problem to multiclass scenario, which was not attempted by previous studies. The highest accuracy under the multiclass scenario was 77.31% and 75.77% by RF. Larger dataset may improve the prediction performance for the multiclass scenario by including data of multiple nations. This will substantially increase the number of observations under multiple categories of dividend policy changes resulting in better training of the model.

CONCLUSION

This study aims to investigate the dynamic nature of dividend phenomenon in India using a holistic approach. Further, the study aims to develop a contemporary model to predict the dividend policy based on modern data-mining techniques. The results demonstrate a substantial decrease in the percentage of dividend-payers and quantum of dividend payments during 2006–2022. COVID-19 affected years of 2021 and 2022 experienced a large decrease followed by a substantial jump in the percentage of dividend-payers and size of dividends. The percentage of firms with positive earnings decreased and then increased. This indicates that these firms stopped paying dividends due to negative earnings and continued to do so even after moving into the positive earnings category. Manufacturing and service sector dominated the dividend-payers category. Analysis of the annual trend in firm characteristics

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reveal that dividend-payers were bigger, older, more mature, more profitable; had higher sales growth, investment avenues, banking relations, institutional shareholding, and lower liquidity of shares in comparison to non-payer firms. Further logistic regression results suggest that larger, older, mature and profitable firms with higher past year dividends, current year earnings, effective tax rate, institutional stake holding, bank monitoring and audit quality are more likely to pay dividends. GDP growth rate, repo rate, income velocity of money, annual percentage change in equity issues, listings and gross fixed assets formation at the macro level increase the likelihood to pay dividends. Firms with higher investment opportunities are less likely to pay dividends. Annual percentage change in debt issues and new project announcements at the macro level decrease the chances of dividend payment. Dividend policy prediction models based on regularization and data-mining techniques found random forest attain the highest prediction accuracy of 90.77% and 77.31% under binary and multiclass scenario.

This study will be helpful for firms' management to understand the evolving trend in dividends and the contemporary forces influencing payment of dividends. It will be useful for portfolio managers and investors to choose the target firms according to the characteristics that are more appropriate for their investment objectives (preference for dividends versus retention of profits). This study also provides a prediction model that can be helpful for firms' management, portfolio managers, retail investors, government, market analysts and other market participants to devise their future actions proactively by leading the market occurrence of dividends.

AUTHOR CONTRIBUTIONS

Conceptualization: Amit Kumar, Pankaj Sinha.
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Investigation: Amit Kumar, Pankaj Sinha.
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Validation: Amit Kumar, Pankaj Sinha.
Visualization: Amit Kumar, Pankaj Sinha.
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APPENDIX A

Table A1. Variable description

S.No.	Variable Name	Variable Description	Variable Code
1	Dividend Payments	Equity dividend to net worth	EDNW
2	Last Year Dividend	Equity Dividend to net worth T–1 period	$EDNW_{T-1}$
3	Earnings	EPS Diluted	EPS
4	Investment Prospects	P/B Ratio	PB
5	Firm Growth	Percentage change in net sales	DNS
6	Firm Profitability	Return on Assets (ROA)	ROA
7	Financial Leverage	Debt to Equity Ratio (D/E)	DE
8	Market Risk	Beta	Beta
9	Firm Riskiness	% change in PAT	DPAT
10	Firm Liquidity	Current Ratio	CR
11	Free cash flows	Net cash flow from all activities/Market capitalization	NCMC
12	Stock Liquidity	Liquidity (shares traded divided by market capitalization	STMC
13	Age of the firm	Natural log of number of years since incorporation	AGE
14	Maturity Stage	Cumulative retained profits divided by total equity/net worth	CRENW
15	Asset Tangibility	Net fixed assets divided by total assets	TANG
16	Firm Size	Natural log of net sales	NS
17	Effective Tax Rate	Corporate tax as a percentage of profit before tax (tax/pretax income)	CTPBT
18	Dividend Taxability	Four different dividend tax regimes during 2006–07, 2007–08 to 2013–14, 2014–15 to 2019–20 and 2020–21 to 2021–22 are represented by 3 dummy variables representing years from the latter 3 tax regimes. These dummy variables take a value equal to 1 if a year belongs to the particulars tax regime, else 0.	TRR_1 TRR_2 TRR_3
19	Audit Quality	Dummy variable is equal to 1 if the auditor is a Big5 Firm for a year and 0 if it is not a Big5 firm.	AUDIT
20	Major Offices Location	Dummy variable is equal to 1 if the location of either the head, corporate or registered office is in Mumbai, Delhi, Kolkata, Chennai, Bengaluru and Hyderabad and 0 for any other city	LOCATION
21	Institutional Ownership	% of institutional holding	NPI
22	Promoter Ownership	% of promoter holding	PRO
23	State Ownership	Government/Private Dummy (1 for govt. and 0 for private)	OWNERSHIP
24	Industry Type	4 dummy variables (representing mining, service, manufacturing and electricity) showed the classification of firms into five Industries (mining, service, manufacturing, electricity and real estate). Dummy variable is equal to 1 if a firm belongs to the particular industry, else 0	MIN SER MANU ELEC
25	Bank Monitoring	Bank debt divided by total debt	BDTD
26	Bank Monitoring	No. of banking relations or bankers in a year	NB
27	Global Financial Crisis Shock	Dummy variable equal to 1 for the period 2007–08 to 2008–09 and 0 for other years.	FC
28	Global Covid 19 Pandemic Shock	Dummy variable equal to 1 for the period 2019–20 to 2021–22 and 0 for other years.	PS
29	Macroeconomic Variable	Gross Domestic Product Growth Rate (at constant prices with base year 2011–12)	GDP
30	Macroeconomic Variable	Inflation Rate (Wholesale Price Index with base 2011–12 spliced series)	WPI
31	Macroeconomic Variable	REPO rate	REPO
32	Macroeconomic Variable	Money supply M3 measure (annual % change)	DM3
33	Macroeconomic Variable	Income velocity of money (GDP spliced series/M3	GDPM3
34	Macroeconomic Variable	Exchange rate measure (annual % change) – RBI Reference rate	DFX
35	Macroeconomic Variable	Marginal Propensity to consume (base 2011–12)	MPC
36	Macroeconomic Variable	GFCF to GDP at constant prices (base 2011–12)	GFCFGDP
37	Macroeconomic Variable	Equity issues annual % change	EQ
28	Macroeconomic Variable	Debt issues (annual % change)	DEBT
39	Macroeconomic Variable	No. of listed companies (annual % change)	NL
40	Macroeconomic Variable	Gross fixed Assets of non–financial companies (annual % change)	GFA
41	Macroeconomic Variable	New Investment projects announced (annual % change)	IP

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